

A Systematic Study of Supervised and Ensemble Learning Approaches for Crop Selection in Smart Agriculture

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Abstract—

Selecting the crop best matched to a field's soil and climate is one of the highest-leverage decisions in agriculture, and one that farmers have traditionally made by intuition or inherited practice. Soil pH together with nitrogen, phosphorus and potassium concentration, and the local temperature, humidity and rainfall regime, jointly determine which crop will flourish and which will fail, and the relationship between those variables and crop performance is neither linear nor independent. Machine learning has therefore become the dominant approach to automated crop recommendation. This paper reviews the field across four technique families — classical supervised learning, ensemble and boosting methods, deep learning and metaheuristic hybrids, and IoT and deployment-oriented systems — and compares twenty-four representative studies published between 2016 and 2026 in terms of method, data source, reported accuracy, advantage and limitation. A generic seven-stage recommendation pipeline is presented and each family is situated within it. The comparison shows that reported accuracy on the standard nutrient-and-climate benchmark has converged in a narrow band between roughly 98 and 99.5 per cent, that boosting and ensemble methods occupy the upper part of that band, and that further gains on the benchmark are no longer the binding constraint on the field. The gaps that remain open are instead the absence of socio-economic and market variables from the decision, the lack of region-specific and long-horizon environmental validation, dataset narrowness and geographic bias, limited interpretability, and the accessibility of these systems to small and resource-poor farmers. These are consolidated into a set of research directions for future work.

Keywords—crop recommendation, soil composition, precision agriculture, machine learning, ensemble learning, XGBoost, Internet of Things, explainable AI, decision support system.

I. INTRODUCTION

The convergence of agriculture and computing has produced precision farming, in which data-driven analysis replaces inherited practice as the basis for cultivation decisions. Soil composition sits at the centre of that shift. The pH of a soil, its nitrogen, phosphorus and potassium concentration, its moisture level and its organic matter content jointly determine which crops can flourish in a given field, and the capacity to recommend a crop accurately from a soil analysis therefore has a direct effect on yield and on the ecological footprint of the operation [11], [12].

The difficulty is that the mapping from soil and climate variables to crop suitability is neither linear nor separable. Nutrients interact: phosphorus availability depends on pH, and potassium uptake is modulated by the nitrogen supply. Climate interacts with soil: the same nutrient profile supports different crops under different rainfall regimes. A heuristic rule set cannot represent those interactions, which is why the field has moved decisively to machine learning, where the interaction structure is learned from data rather than specified in advance [10], [13].

A large and rapidly growing literature now addresses this problem, using techniques that range from a single decision tree to multimodal deep networks fusing soil imagery with tabular nutrient profiles, and deployment targets that range from a cloud service to a microcontroller in the field. The variety makes the literature difficult to navigate: studies differ in dataset, in crop coverage, in evaluation protocol and in what they treat as the output of the system, so a reported accuracy figure from one study is rarely comparable with another.

This review makes four contributions. First, it organises the literature into four technique families and situates each surveyed study within that taxonomy. Second, it presents a generic seven-stage recommendation pipeline against which any of the surveyed systems can be described. Third, it compares reported accuracy across the surveyed systems and shows that the benchmark figure has converged, so that architectural novelty now yields diminishing returns. Fourth, it identifies the gaps that remain once benchmark accuracy has saturated and states the research directions that follow.

Section II presents the taxonomy and the generic pipeline. Section III reviews the literature by family. Section IV compares reported performance. Section V states the research gaps and Section VI concludes.

II. TAXONOMY AND GENERIC PIPELINE

Fig. 1 organises crop recommendation research into four families. The classical family applies a single supervised learner — decision tree, k-nearest neighbour, support vector machine, naive Bayes or logistic regression — to a tabular soil and climate record. The ensemble family aggregates many weak learners, either by bagging as in random forest or by sequential boosting as in XGBoost, CatBoost and gradient boosting. The deep and hybrid family uses neural architectures, often combined with a metaheuristic optimiser for feature selection or hyperparameter search, and increasingly fuses more than one modality. The deployment family is concerned with the conditions of practical use: sensor-driven real-time input, execution on edge hardware, and explanations that a farmer or agronomist can act on.

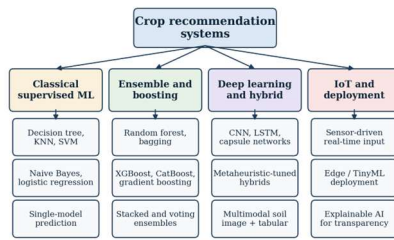


Fig. 1. Four-family taxonomy of crop recommendation systems.

The families are cumulative rather than exclusive: a deployment-oriented system still selects a learner from one of the first three families, and hybrid systems routinely place a metaheuristic in front of an ensemble. What distinguishes a contemporary system is therefore the combination of stages it selects, and Fig. 2 gives the pipeline within which those choices are made.

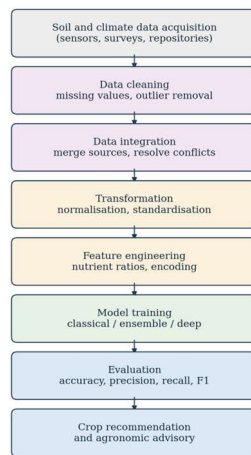


Fig. 2. Generic pipeline for a crop recommendation system.

Acquisition supplies the soil and climate record, from a sensor network, a field survey or a public repository. Cleaning removes missing values and outliers, either by imputation with the mean, median or mode, or by a predictive method, and by an interquartile-range or z-score filter. Integration merges heterogeneous sources and resolves inconsistent naming and measurement scales. Transformation normalises numeric fields such as pH and nutrient concentration to a common range and standardises them to unit variance, so that no variable dominates by virtue of its scale. Feature engineering derives new variables such as nutrient ratios and encodes categorical fields. The model is then trained and evaluated, and the recommendation is issued. The literature differs mainly in the last two stages; the first five are common to almost every system surveyed.

III. LITERATURE REVIEW

A. Classical Supervised Learning

Gosai et al. proposed a crop recommendation system built on conventional supervised learners and motivated it by the limitations of intuition-based selection, which frequently leads to financial loss [15]. Banerjee and Mondal evaluated decision tree, logistic regression, naive Bayes, random forest and support vector machine on region-wise weather data, with the objective of assisting farmers to choose a crop appropriate to local conditions [19]. Ed-daoudi et al.

assessed five learners on soil nutrient level, temperature and precipitation for Moroccan farmers and identified random forest as the most effective, while noting that limited data availability constrained the result; the stated aim of delivering a free and open-source precision-farming tool illustrates the accessibility concern discussed in Section V [18]. Ommane et al. reviewed the evolution, principal features and challenges of recommender systems in crop selection and observed the absence of a comprehensive classification scheme for the algorithms and features in use — a gap that the taxonomy of Section II is intended to address [10].

B. Ensemble and Boosting Methods

Paithane applied random forest to crop recommendation, averaging many decision trees over subsets of the data to improve accuracy and stability, and contributed a web application and a GPS-based location identifier for retrieving environmental data [13]. Apat et al. evaluated fourteen classifiers spanning the classification, regression and boosting families, and reported CatBoost as the best performer at 99.51% accuracy, with Gaussian naive Bayes leading on ROC and Matthews correlation coefficient; the study emphasised soil fertility management and integrated nutrition management as the agronomic context [12]. Gopi and Karthikeyan proposed a multimodal machine learning model combining recommendation with yield prediction, and reported high accuracy alongside a dependence on data quality and a restriction to specific crops [9]. More recent work has extended the family: Chamoli et al. compared logistic regression, support vector machine, random forest and gradient boosting and found random forest strongest at 99.32% [2]; Paliwal and Upadhyay trained XGBoost, logistic regression, k-nearest neighbour, decision tree and gradient boosting for joint crop and fertiliser recommendation [3]; and a further study benchmarked random forest, XGBoost and multi-layer perceptron on soil and climate parameters with an explicit emphasis on combining predictive performance with interpretability [4]. A comparative evaluation of Gaussian naive Bayes, random forest, XGBoost, multi-layer perceptron and a convolutional network over 2,200 instances covering twenty-two crops reported Gaussian naive Bayes as the most effective at 99.54% accuracy and the convolutional network as comparatively weak, which is a useful corrective to the assumption that deeper is better on tabular data [5]. The gradient-boosting formulation that underlies most of this family is due to Chen and Guestrin [8].

C. Deep Learning and Hybrid Models

SSL et al. proposed an intelligent recommendation system using deep learning and noted data complexity as the principal limitation, suggesting transfer learning for data efficiency [14]. Kiruthika and Karthika combined improved distribution-based chicken swarm optimisation for feature selection with a weight-based long short-term memory network for prediction, collecting and conditioning climate data before the learning stage [17]. A channel capsule network stacked with a dilated bidirectional LSTM has been proposed for joint prediction of crop water requirement and crop recommendation, using IoT data conditioned by normalisation, missing-value imputation and one-hot encoding, and coupling a gated residual autoencoder with a chaotic optimisation

algorithm. Sharmin and Kiekintveld took a different route, integrating climate data, soil characteristics and historical yield in a Bayesian belief network, which supplies probabilistic reasoning over parameter impact, accounts for uncertainty and adapts to a farmer's stated preferences and constraints [22]. Recent work has added explainability and modality fusion: a gradient-boosting model tuned by Krill Herd Optimisation and equipped with explainable outputs reports 99.27% accuracy, precision and recall [1], and AgroSense fuses convolutional and transformer-based soil image classification with structured nutrient analysis, reporting 98.0% with statistically validated improvement [6].

D. IoT and Deployment-Oriented Systems

Senapaty et al. proposed the IoTSNA-CR model, integrating Internet of Things sensing, cloud storage and a custom analysis algorithm, delivered through an Android application so that support is continuous rather than episodic; the MSVM-DAG-FFO algorithm recommends crops while optimising soil nutrient usage [11]. Jeyanathan et al. built a crop recommender on an STM32 ARM processor simulated in Proteus and implemented on a Nucleo board with humidity, pH and temperature sensors, displaying the recommendation on an LCD and through a mobile application — an end-to-end demonstration of the sensing-to-advice loop [16]. A recent deployment-oriented review surveys low-cost, low-power edge AI and TinyML for resource-constrained farming and observes that although random forest implementations on ultra-low-cost microcontrollers achieve model size reductions approaching ninety-nine per cent, most such systems operate with static inference pipelines and lack adaptive learning or distributed coordination [7]. That review also confirms the Kaggle nutrient-and-climate corpus as the most commonly used benchmark for the task [25].

E. Agronomic and Fertiliser Recommendation

A parallel literature addresses what to apply rather than what to plant. An electronic agricultural record system has been proposed that unifies heterogeneous datasets in a Hive and Elasticsearch data warehouse and derives statistical recommendations for nitrogen, phosphorus and potassium quantities for the most widely grown crops, with the explicit objective of balancing crop nutrition against environmental impact. Morais et al. synthesised biochar-based phosphate fertilisers from coffee husk and low-grade phosphate rock and tested their agronomic performance on maize and Brachiaria grass, addressing phosphorus use efficiency in Oxisols [20]. Mithra and Suhasini combined bagging, random forest, linear regression and naive Bayes for oilseed yield forecasting with an organic-manure recommendation delivered through a graphical interface [21]. Friedman questioned the common practice of treating the crop evapotranspiration rate as a surrogate for the recommended irrigation rate, calling for an integrated treatment of soil, plant and climate interaction [23], and Gallardo et al. calibrated the VegSyst model for macronutrient uptake in pepper and muskmelon and developed a decision support system that reduces excessive nutrient application [24].

F. Related Machine Learning Work by the Authors' Group

The methodology reviewed here has been applied by the present group across several adjacent recommendation and tabular-prediction problems. Recommendation systems have been built from client profiles for e-commerce [27] and through hierarchical K-means clustering for social recommendation [28], both of which share the profile-to-recommendation structure of the crop task. Tabular forecasting and regression pipelines have been developed for railway passenger demand [29] and for financial time series using linear regression [30], neural networks [31], support vector machines [32] and genetic algorithms [33], together with a survey of that literature [34]. Tree and ensemble classifiers have been applied to credit card fraud detection [35], cancer prediction with random forest and deep learning [36], and intrusion detection with principal component analysis and random forest [37], while machine learning has been used for rare disease identification from electronic health records [38]. Sequence and vision models have been applied to network traffic prediction [39], transfer-learning-based object detection [40] and convolutional glaucoma detection [41]. The methodological commitments visible across that work — disciplined conditioning of tabular input, explicit feature construction, and comparative evaluation of several learners under a fixed representation — are the perspective from which this review is written.

TABLE I. Summary of Representative Crop Recommendation Studies

Ref.	Year	Method	Advantage	Limitation
[9]	2023	Multimodal ML	Data integration, high accuracy	Data quality; specific crops only
[10]	2023	Review of recommender systems	Comprehensive survey	No real-world evaluation
[11]	2023	IoT + cloud, MSVM-DAG-FFO	Real-time sensing	Infrastructure and sensor upkeep
[12]	2023	CatBoost among 14 classifiers	99.51% accuracy	Data privacy concerns
[13]	2023	Random forest	Ensemble stability, web app	Limited interpretability
[14]	2023	Deep learning	Learned representation	Data complexity
[15]	2021	Classical supervised ML	Early work in the area	Data quality
[16]	2023	ML + IoT on STM32	End-to-end hardware demo	Deployment cost and scaling
[17]	2023	IDCSO + weighted LSTM	Optimised feature selection	Infrastructure dependence
[18]	2023	Five learners, RF best	Local context, open source	Limited data availability
[19]	2023	Region-wise weather + ML	Uses weather data	Weather data availability
[20]	2023	Biochar phosphate fertiliser	Soil nutrient management	Specific soil types only
[21]	2023	Bagging, RF, LR, NB	GUI-based advisory	Oilseed crops only
[22]	2023	Bayesian belief network	Uncertainty, preferences	Optimisation scope limited
[23]	2023	Evapotranspiration analysis	Irrigation optimisation	Irrigation only
[24]	2023	VegSyst-DSS v2	Nutrient decision support	Greenhouse crops only
[1]	2026	Gradient boosting + KHO + XAI	99.27%, explainable	Single benchmark corpus
[2]	2026	LR, SVM, RF, GB	RF best at 99.32%	No field validation
[3]	2026	XGBoost, LR, KNN, DT, GB	Crop and fertiliser jointly	Benchmark corpus only

Ref.	Year	Method	Advantage	Limitation
[4]	2026	RF, XGBoost, MLP	Performance + interpretability	Tabular input only
[5]	2025	GNB, RF, XGBoost, MLP, CNN	GNB best at 99.54%	CNN weak on tabular data
[6]	2025	CNN + transformer + ML fusion	Multimodal, 98.0%	Soil imagery required
[7]	2026	Edge AI / TinyML review	Deployment orientation	Static inference pipelines

IV. COMPARATIVE PERFORMANCE

Fig. 3 plots the accuracy reported by representative systems across the families of Section II.

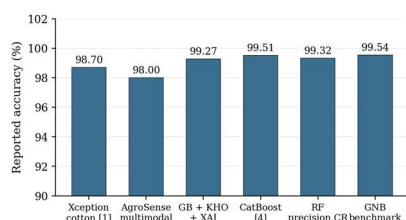


Fig. 3. Accuracy reported by representative crop recommendation systems. Corpora differ, so the comparison is indicative.

The distribution is strikingly narrow. Every system plotted falls between 98.00% and 99.54%, a total spread of 1.54 percentage points across four technique families and a decade of architectural development. Boosting and ensemble methods occupy the upper part of the band — CatBoost at 99.51% [12], random forest at 99.32% [2], gradient boosting with metaheuristic tuning at 99.27% [1] — but Gaussian naive Bayes, the simplest probabilistic learner in the comparison, reaches 99.54% [5], and the multimodal deep system sits at the bottom of the band at 98.00% [6]. The correct reading is not that naive Bayes is the best model for the task; it is that the standard benchmark no longer discriminates between models. When six architectures of radically different capacity all score within one and a half points of each other, the residual differences are dominated by partitioning, preprocessing and random seed rather than by the learner.

Fig. 4 shows how the surveyed studies distribute across the four families.

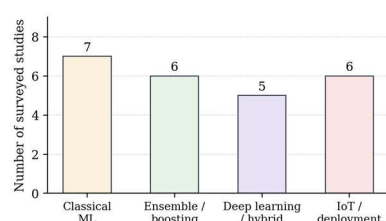


Fig. 4. Distribution of the surveyed studies across technique families.

The distribution is close to uniform, which is itself informative: no family has displaced the others, and the classical family remains as well represented in the recent literature as the deep one. That pattern is consistent with the accuracy convergence of Fig. 3. Where a simple learner matches a complex one on the benchmark, the choice between them is decided by cost, interpretability and deployability rather than by accuracy, and the recent shift toward edge deployment [7] and explainability [1] reflects exactly that reordering of priorities.

Two methodological cautions apply to both figures. First, the corpora differ: some studies use the 2,200-instance nutrient-and-climate benchmark [25], others regional weather records [19] or georeferenced soil surveys, and accuracy is not transferable between them. Second, very few studies report confidence intervals or repeated-run variance, so a difference of two tenths of a point between two published systems carries no demonstrated significance. Controlled benchmarking under a fixed partition and preprocessing protocol, of the kind now emerging in adjacent fields, is the appropriate remedy.

V. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite the maturity evident in Section IV, several gaps remain open.

- Socio-economic variables. Market trends, the economic position of the individual farmer and regional agricultural policy strongly influence crop selection, yet almost no surveyed system admits them as input. A recommendation that is agronomically optimal but economically unviable will not be adopted.
- Long-horizon environmental impact. Soil health degradation, biodiversity loss and water resource depletion follow from repeated cultivation decisions, and the surveyed systems optimise a single season without reference to them.
- Region-specific climate adaptation. Climate impacts are local, but most work uses broad climate data and offers no strategy tailored to a specific agro-ecological zone.
- Integration of traditional knowledge. Practices refined over generations encode local information that no public dataset contains, and combining them with learned models remains largely unexplored.
- Accessibility for small and resource-poor farmers. Usability and cost bound adoption more tightly than accuracy does; the TinyML and edge direction addresses this but is still underdeveloped for the recommendation task [7].
- Dataset narrowness and geographic bias. The dominant benchmark covers twenty-two crops under one set of agro-ecological conditions; newer georeferenced multimodal corpora are only beginning to broaden this.
- Interpretability. A farmer acting on a recommendation needs to know which nutrient or climate variable drove it; explainable formulations are recent and not yet standard [1].
- Real-time processing and predictive analytics. The ability to revise a recommendation as conditions change during a season, rather than issuing it once before sowing, is largely absent.

VI. CONCLUSION

This paper reviewed machine learning based crop recommendation across four technique families — classical supervised learning, ensemble and boosting methods, deep learning and metaheuristic hybrids, and IoT and deployment-oriented systems — covering twenty-four representative studies published between 2016 and 2026, and presented a generic seven-stage pipeline against which any of them can be described. The comparative analysis

showed that reported accuracy has converged into a band between 98.00% and 99.54%, that the four families are represented almost uniformly in the recent literature, and that the residual differences between published systems are not large enough, given the absence of variance reporting, to establish the superiority of any one architecture on the standard benchmark.

The consequence for future work is a reordering of priorities. Additional accuracy on the existing benchmark is no longer the binding constraint; what limits the field is the narrowness of the decision being modelled and of the data on which it is trained. Future systems should admit socio-economic and market variables alongside agronomic ones, evaluate over multiple seasons and agro-ecological zones rather than a single partition of a single corpus, quantify long-horizon effects on soil health and water resources, run within the cost and power budget available to a small farmer, and explain each recommendation in terms of the soil and climate variables that produced it. Standardised benchmarking protocols reporting repeated-run variance would allow genuine methodological progress to be distinguished from partitioning noise.

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